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Deep Learning-based Land-cover Change Detection in Remote-sensing Imagery

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ABSTRACT

With the significant advancement in deep-learning methods and their feature representation, deep-learning methods are more prevalent in solving change-detection tasks. The prime purpose of change detection is to detect the changes on the surface of the earth. In this work, an end-to-end encoder-decoder architecture is used to detect the changes in the land cover. The proposed method uses residual U-Net to find land-cover image changes. The UNet structure is used as the backbone of the network. The effectiveness of the proposed method has been experimented through LEVIR-CD datasets. The results showed that the proposed method outperforms the state-of-the-art techniques and gives reliable results. These techniques can be used to examine changes in the earth's crest due to natural events, such as landslides, earthquakes, erosion and geo-hazards or human activity, like mining and development.

KEYWORDS: Change detection, Remote sensing, Residual UNet, Deep learning, Land cover, Climate.

INTRODUCTION

Change detection is a method for determining how the characteristics of a particular region have changed over time. Aerial pictures or satellite imageries of the area obtained on different dates are frequently used to spot changes. With a wide range of remote sensing data, it is possible to find the differences in the land surfaces. Change detection has been frequently utilized to analyze shifting agriculture, deforestation, urbanization and the effects of natural catastrophes, such as tsunamis and earthquakes (Shatnawi et al., 2022). It has a broad scope of interest due to its extensive usage in real-world applications. So, the focus on change detection has attracted the interest of many researchers around the globe.

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Earlier, long-and short-term biodiversity and Geographic Information System (GIS) methods were used to investigate Land Use Land Cover (LULC) variations in an area (Mishra et al., 2020). Nowadays, remote sensing data-based change detection methodologies are used primarily. These methodologies are entirely based on satellite datasets and data is obtained through different types of sensors; namely, optical, microwave and high/low-resolution sensors. The satellite datasets clearly describe land-cover changes over a while. Due to this, researchers have derived many algorithms and methodologies for finding the changes from remote-sensing data (Shafique et al., 2022).

Satellite photos are photographs of the earth captured by imaging satellites operated by governments and companies worldwide (also known as earthobservation imagery, space-borne photography or simply satellite pictures). Landsat pictures have bands of information: coastal, RGB (red, green, blue), NIR (near-infrared), SWIR 1-2 (shortwave infrared), panchromatic and cirrus. The remote-sensing images are in the form of synthetic aperture radar (SAR) images, hyperspectral images, high-resolution multispectral images, heterogeneous images (Li et al., 2021) and very high-resolution (VHR) satellite images. To process these images, various pre-processing techniques are adopted by researchers. For example, despeckling, denoising, image filtering, image registration, radiometric corrections and geometric corrections are the standard pre-processing techniques for image types (Mishaa et al., 2021; Jennifer et al., 2022).

Many traditional change-detection methods are available in state-of-the-art techniques. However, object-based image analysis and threshold methods are mainly applied to find the changes in the images. In addition, supervised and unsupervised learning techniques depend on hand-crafted feature-extraction steps (Volpi et al., 2013). These steps limit the input image information and yield low performance for finding the land-cover changes. Nowadays, deep learning-based change-detection methods are the hotspot in remote-sensing research (Sun et al., 2021a,b; Yang et al., 2022). The deep-learning networks automatically derive the non-linear and hierarchical features from the input image, which overcomes the significant limitations of traditional machine-learning methods. Due to their incredible learning capabilities, deep-learning models give the link between remote-sensing images and their geographical elements (Seydi et al., 2021).

Chen et al. (2020) used convolutional neural networks (CNNs) for change-detection tasks. The attention mechanism is skilfully employed in the change-detection job. The data-dependent up-sampling approach is used simultaneously, increasing network accuracy and significantly reducing computation. Experimental findings demonstrate that the proposed network has a more vital anti-noise ability and can prevent erroneous detection to some level in two-phase photos of Yinchuan City. Zheng et al. (2021) investigated cross-layer convolutional neural network (CLNet). The cross-layer blocks (CLBs) were developed to incorporate multi-scale features. The multi-level context information allows the proposed CLNet to reuse extracted feature information and accurately record a pixel-wise change in complex circumstances. Building change detection and aerial building change detection are discussed elaborately.

A two-dimensional convolutional neural network was used to handle the information in hyperspectral images (Wang et al., 2018). A variety of convolution kernels was used to exhibit the spectral features from the input images. The fully connected layers were utilized to fuse different parts and to find the change maps. Gong et al. (2015) elaborated on a deep learning-based change-detection method for multi-temporal SAR images (Li et al., 2021). The deep-learning network generates the change-detection map directly from the input images. The change-detection process is considered a classification problem. Initially, the input data is pre-classified with labels and the network is learned with image features. The results of this proposed method are compared with clustering-based methods.

Two convolution neural networks are used to extract the features from high spatial-resolution images and compared with the help of contrastive loss functions. The resultant feature vector is used to find the changes in the land cover (Zhu et al., 2022). Without relying on labelled data, Touati et al. (2020) suggested a deep sparse residual model that can recognize changes and abnormalities in image characteristics. Convolutional neural networks (CNNs) and auto-encoders are used in this method to train deep representations of the image data. A residual learning strategy is then used to detect changes and abnormalities in the image features. Jiang et al. (2020) performed change detection on images taken with optical and SAR (Synthetic Aperture Radar) sensors. The deep-learning method is used to produce a homogeneous feature representation that captures variations in the images.

Mou et al. (2018) investigated a hybrid method that consists of a convolution neural network and a recurrent neural network to find the spatial-temporal features for change detection (Chen et al., 2020, 2021). Long-short-term memory (LSTM) and three-dimensional convolution neural networks are used in Re3FCN (Song et al., 2020). This method integrates the advantages of both deep-learning architectures. The training data is generated with the help of PCA techniques. The spectral—spatial-temporal information is retrieved from the multi-temporal images. It also identifies the multiclass changes while implementing fully connected layers. As a result, hybrid networks yield better results than single networks.

Deep-learning techniques are suitable for assessing the large volumes of data generated by modern monitoring systems, like satellite imagery, GPS and seismic sensors. Processing complex and enormous datasets is a task for which deep-learning techniques are particularly well suited. By combining several data sources with state-of-the-art deep-learning algorithms, researchers can learn the changes happening in the earth's crest and the underlying processes that are accountable for these changes. Deep-learning methods can locate areas of change, estimate the size of changes and forecast future changes by comparing images of the earth's crest taken over time. This work deals with change-detection techniques by modified UNet architecture. The next section elaborates on the detailed deep-learning methodology for change detection. Then, the results of the proposed method are showcased and the final section of the study gives the concluding statements and future directions. The experimental work is carried out for LEVIR-CD datasets.

METHODOLOGY

This section elaborates on the detailed methodology of the proposed change-detection method. The overall view of change detection is illustrated in Figure 1.

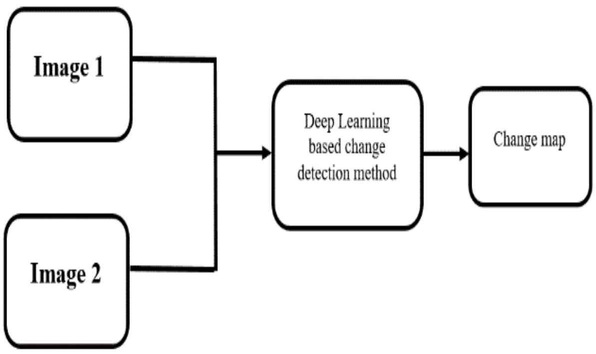

Figure (1): General methodology of the image-based change-detection technique

Supervised learning methods can detect and locate targets quickly. This work also uses the type of semantic segmentation for change detection. The UNet is a convolutional neural network that was created to identify changes. On a current GPU, detecting changes in the surroundings of a 512x512 picture takes less than an alternate. The "fully convolutional network" is the source of the UNet design. The network's armature was streamlined and expanded to manage with lower training prints and produce more precise discoveries. The up-sampling Net's component features many feature channels, allowing to send context information to higher-resolution layers. As a result, the enlarged half of the route is nearly symmetrical to the contracted half, resulting in a U-shaped structure. Without any ultimately linked layers, the network uses a good portion of each convolution.

UNet follows the encoder and decoder structure. The encoder block compresses the input images as a dense feature vector. The feature vector dimension is reduced to get deep discriminative representations. The feature vector is spatially expanded to reach the segmented image on the decoder side. The transposed convolution and bilinear interpolation are employed in the decoder to match with original input dimensions. Because it has a contracted path and an enlarged path, the network is U-shaped. Adam is the best adaptive optimizer in the vast majority of cases. The Adam optimizer uses a combination of two gradient descent methods. This approach speeds up the gradient descent process by considering the 'exponentially weighted average of the gradients. The adaptive learning rate is perfect for sparse data.

The constricting route is a conventional convolutional network with complicated operations followed by a rectified linear unit and a maximum pooling operation. The spatial information is reduced during compression, but the point information is increased. The extended pathway integrates point and spatial data through over-complications and trains high-resolution characteristics from the narrowing path. In this work, residual UNet is used to determine the change detection. The residual UNet block diagram (Alom et al., 2019) is given in Figure 2.

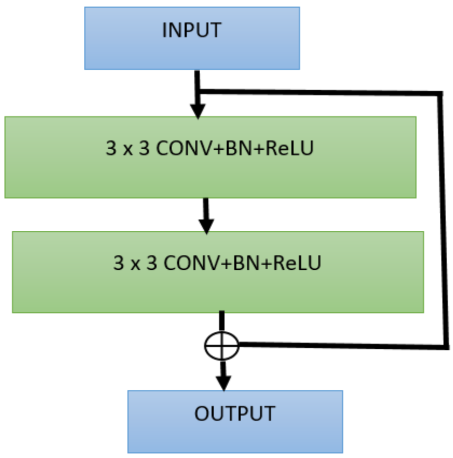

Figure (2): Block diagram of residual UNet

The structure of the proposed residual UNet network for change detection is given in Figure 3. The dashed lines highlight the residual connections of the network. In the input layer, the image is divided into the size of 256x256x3 and these patches are given into the network, while the detection result is obtained in the output layers. The results show the positively changed, the negatively changed and the unchanged regions.

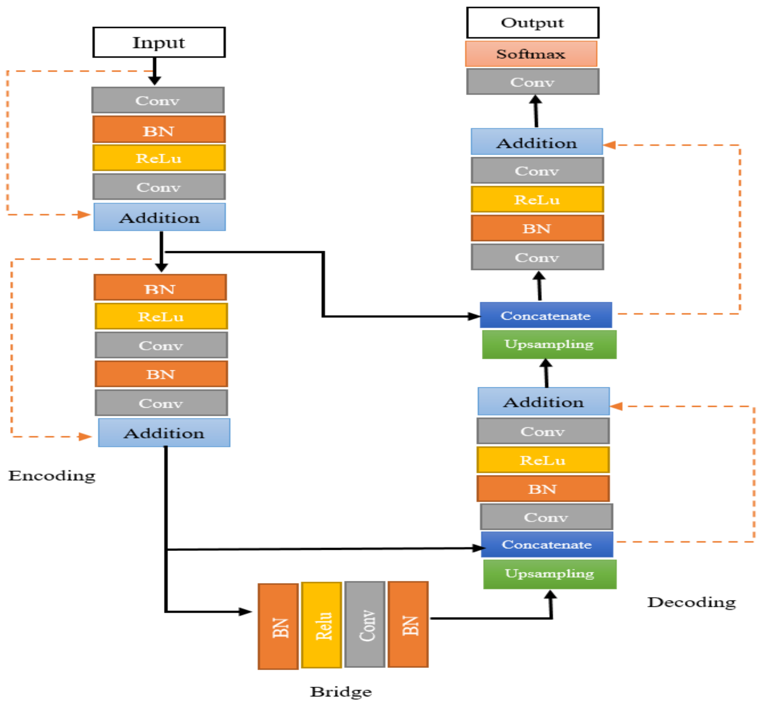

Figure (3): Residual UNet structure for change detection

The channels change from 1 to 64 in the contracting phase as the convolution process increases the image depth. Padding concerns caused a reduction in size from 256x256 to 128x128. The max-pooling method, which reduces the size of the image by a half, is indicated by the arrow going down. Three times more, the process is repeated. The contracting route consists of a typical convolutional network with several convolutions, followed by a rectified linear unit and a max-pooling operation. During contraction, the spatial information is reduced while the feature information is increased.

When these feature maps are subjected to 2D convolution, two-dimensional patches of surrounding features are formed. A convolution kernel is then used to turn the patches into a one-dimensional vector representing the output depth. The vectors are then spatially rebuilt into a two-dimensional output map representing all the data. Several filters are used in the convolution layers to find the responses of the neurons. A transposed convolution matrix will be used to up-sample a smaller matrix into a bigger one. The dimensions of the filters are always lesser than the sub-input images—the filter iterates across the images, linking to specific places in the input sub-images. Based on the activation functions set for the filters, the input is utilized to compute new pixel values.

Before performing a new computation, batch normalization is used to scale the output from the convolution layer to the same. The current batch's mean and standard deviation parameters normalize each input layer. In the training phase, the variation of activation-function values is reduced. To minimize overfitting and generalization errors, unnecessary neurons might be silenced during the iterative phase. To maintain the output of each node in a hidden layer, a dropout value of 0.5 is frequently utilized. The concatenate layer connects image data from the contracting to the expanding paths. Due to the simplicity of the original data to new data during the contracting process, the residual UNet models leverage data from prior layers to produce a more accurate forecast.

EXPERIMENTAL RESULTS AND DISCUSSION

Dataset Description

The input image is hyperspectral and the multispectral satellite dataset is acquired from LEVIR CD datasets and displays two sets of pictures from 2002 and 2018 with 637 image dyad markers in colourful styles of image accession for remote-seeing operations. Multiple spectral bands are used to create multispectral and hyperspectral imaging systems. LEVIR-CD is a novel distant-sensing structure change discovery dataset with a considerable size. The new dataset would serve as a new benchmark for evaluating change-discovery (CD) algorithms, particularly those based on deep literacy (Chen et al., 2021). LEVIR-CD comprises 637 Google Earth (GE) image patch dyads with a resolution of 0.5 m/pixel and a size of 1024*1024 pixels. Significant land-use changes, particularly construction expansion, may be seen in these bi-temporal photos that span 5 to 14 times. LEVIR-CD has many buildings, including manor houses, loft apartments, tiny garages and enormous storage facilities. The structure changes, such as structural growth and structural decline, are there in the images. These bi-temporal images are illustrated by remote-seeing image-interpretation experts using double markers.

Figure (4): Images of LEVIR-CD dataset for the years 2002 & 2018

The LEVIR-CD, which is fully annotated, provides a collection of specific change-structure examples (Chen et al., 2020). The satellite-picture dataset for remote-sensing operations uses airborne detectors with varying spectral, temporal, spatial and radio meter resolutions from multi-coloured satellite configurations. The collection comprises 637 picture pairings at a resolution of 0.5m from the LEVIR-CD datasets. LEVIR-CD contains bi-temporal pictures from 20 distinct places around Texas, including Austin, Lake-way, Bee Cave, Buda, Kyle, Manor, Pflugerville, Dripping Springs, among others. Figure 4 shows the geographical distribution of our new dataset and an expanded picture patch. Our picture data was gathered between the years 2002 and 2018. Various regions may have images shot at different periods. It is opined that the inclusion of seasonal and lighting fluctuations in the future dataset might aid in developing effective styles that could reduce the influence of inapplicable alterations on real-world changes. It was also used to sort and classify the various accessories. The pixels in each diapason were examined using satellite photos. It may also be used to discover and follow any item.

The imaging spectroscope is another name for satellite film land. Hyperspectral detectors are capable of detecting and verifying molecule immersion. The enhanced spectral resolution of satellite photos is utilized to find, discriminate and inspect the facial accoutrements, concluding the natural and chemical processes. Satellite photos calculate an object's light emigration, discovery and shadowing, detecting infrared and far-infrared waves in short and long wavelengths. Every pixel in hyperspectral pictures has its uninterrupted diapason monitored. Satellite images also identify minerals, soil coffers and backgrounds and characterize terrestrial land, agricultural land, comeuppance, dry land, wetland and artificial particulars. In addition, the atmosphere, ecology, geology, coastal waters, ice/snow, biomass burning and announcements are monitored. The sample images of the LEVIR-CD dataset are given in Figure 4.

Details of Implementation

The deep neural network is implemented using Kears with Tensorflow as the backend. The model is trained using NVIDIA GTX 1050 Graphical Processing Unit (GPU) with a 4 GB memory. An adaptive moment estimation (Adam) optimizer is used because of its minimal tuning parameters. The hyper-parameters of batch size are tested for 16 -25; epochs are varied from 30-50 and the learning rate is fixed at 0.0001. All these hyper-parameters are chosen after many trials, which will give an adequate performance. The activation function of RELU is used for network training. The training parameters are adopted concerning the available resources.

Quantitative Evaluation

The qualitative results of the proposed method are highlighted in Figure 5. Figure 6 shows the linear regression plot of change-detection area of the proposed method and ground truth of LEVIR-CD dataset. The experimental work is carried out by using residual UNET for visualizing robustness of the proposed framework to detect the changes in the cover images. The change-detection zone specifies a correlation of R^2=0.271 in the linear-regression analysis.

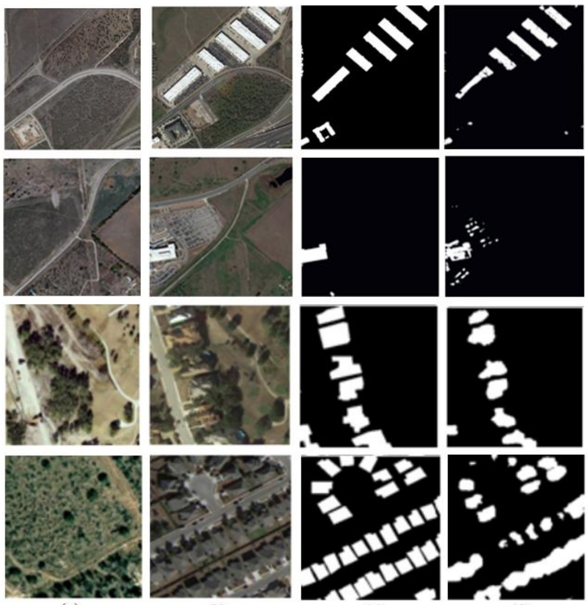

Figure (5): Qualitative results of proposed work, (a) Pre-change image, (b) Post-change image, (c) Ground truth and (d) Residual UNet

The quantitative analysis is based on precision, recall, F_measure and accuracy metrics. Precision is the proportion of relevant occurrences among the retrieved instances (also known as positive predictive value). Precision refers to the amount of detail with which a quantity is expressed. It expresses the proximity of two or more measures to one another. Precision is not synonymous with accuracy. Precision is the degree to which similar measurements of the same item are as near as possible. It highlights the average of input images that are correctly identified to the total number of inputs that are precisely and non-correctly identified by the reference. It is calculated by Equation (1).

$$\text{Precision (P)} = \frac{\text{true positives}}{(\text{true positives } + \text{false positives.})} = \frac{\text{TP}}{(\text{TP} + \text{FP})} \quad (1)$$

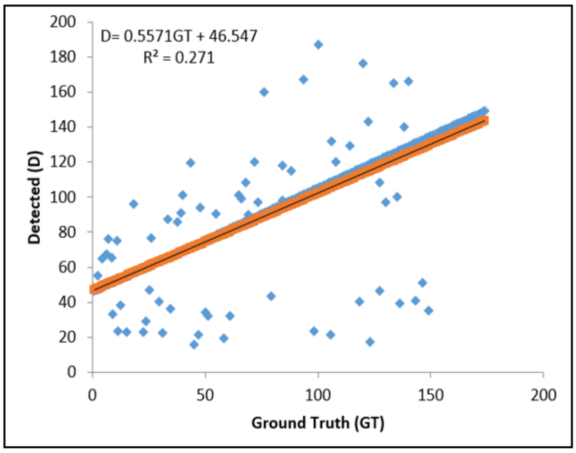

Figure (6): Linear-regression results of change areas detected by the proposed work and ground truth

Recall is described in Equation (2). It is defined as the average number of inputs correctly identified out of the total number of correctly and non-correctly identified inputs.

$$\text{Recall (R)} = \frac{\text{true positives}}{(\text{true positives} + \text{false negatives})} = \frac{\text{TP}}{(\text{TP} + \text{FN})} \quad (2)$$

F_measure is described in Equation (3). It is the harmonic mean of precision and recall. To get a high F_measure score, the value of precision and recall must be increased. If the value of the F_measure score is 1, it is classified as the best and if it reaches 0, it is ranked as the worst.

$$F_{Measure} = \frac{2 \times \text{Precision} \times \text{Recall}}{(\text{Precision} + \text{Recall})} = \frac{2 \times P \times R}{(P + R)} \quad (3)$$

Table 1. Comparative analysis of proposed and state-of-the-art methods

Reference	Method	Precision (%)	Recall (%)	F1-score	Accuracy (%)
Chen et al. (2020)	U-Net (DUpsamplng)	-	0.697	0.743	79.6
Chen et al. (2022)	Siamese Res U-Net	43.81	70.54	0.54	94.45
Peng et al. (2019)	U-Net++	89.54	87.11	0.875	96.73
Chen et al. (2017)	DeepLabv3	77.30	86.00	0.821	98.10
Proposed	Residual UNet	86.12	80.34	0.825	98.76

The results of change detection are commonly shown in binary maps. The dark portions highlight the unchanged area, while the white portions show the changed area. Overall accuracy is the ratio of correctly classified pixels concerning the overall pixels. The performance metrics of precision, recall, f-measure and accuracy of the proposed method are highlighted in Table 1.

Comparative Study

In order to showcase the benefits of the supervised-learning method, the performance of the supervised-learning method is compared with other methods. The performance metrics of the proposed work are precision, recall, f1-measure and accuracy. All these metrics are computed for the proposed work and compared with those of state-of-the-art methods in order to show the benefits statistically. The results of the proposed method are compared with those of four state-of-the-art change-detection methods. Long et al. (2021) elaborated on the change detection with the help of data-dependent upsampling of the UNet method. The network is applied for the Yinchuan change-detection task. Table 1 highlights the comparison results of the proposed and state-of-the-art techniques.

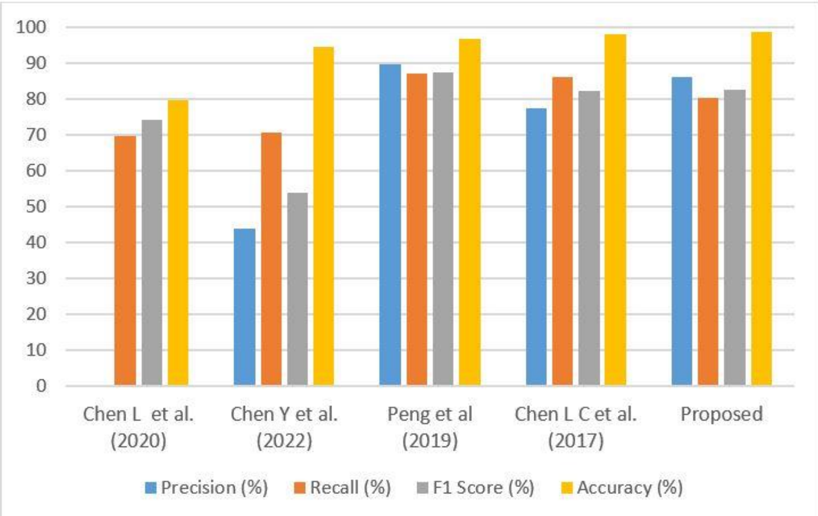

Figure (7): The performance metrics' comparison of the proposed and state-of-the-art methods

Chen et al. (2021) explored the change-detection method based on Res UNet and vector quantization. The multiview remote-sensing image dataset is used for the experimental dataset. The results show a significant performance in terms of contrastive learning. Peng et al. (2019) discussed the change detection for very high-resolution satellite images. The multi-scale feature maps with various semantic levels are combined to find the images' changes. This method highlights the difference and no-changes in the map. All the comparison methods used UNet as the backbone network. UNet and DeepLabv3 are the semantic segmentation networks primarily used in change-detection tasks. The quantitative comparison results are directly taken from the original literature. Figure 7 shows the chart of comparative analysis with the proposed method in terms of precision, recall, F1-score and accuracy.

DISCUSSION AND ANALYSIS

The residual UNet combines the advantages of residual connections and UNet architecture. It has been demonstrated to perform effectively on a variety of computer-vision tasks, including semantic segmentation, the cornerstone of detecting changes in land cover. LEVER-CD images are remote-sensing datasets that offer high-resolution photographs of the surface of the earth. In remote sensing, it is essential to identify changes in land cover. The following are the prime advantages of utilizing residual UNet for LEVER-CD datasets to detect land-cover change.

Residual UNet makes use of skip connections to transfer data from one layer to another without sacrificing spatial information. With the aid of this capability, residual UNet is able to make efficient use of the data at hand and identify any long-range dependencies. Residual UNet has demonstrated great precision in a range of computer-vision applications, including semantic segmentation. This qualifies it as a viable choice for LEVER-CD datasets in land-cover change detection. When compared to typical UNet architectures, residual UNet requires less training iterations to reach excellent accuracy. This is due to that residual UNet's has a smaller number of layers and usage of residual connections to transmit data between layers, which lowers the probability of vanishing gradients.

Residual UNet can handle missing data or noisy images with ease, because it is noise-resistant. In LEVER-CD datasets, which may contain missing or noisy data due to cloud cover or other environmental conditions, this makes it an excellent candidate for land-cover change detection. As a result of its capacity to effectively utilize data, shorten training times, manage missing or noisy data and achieve high accuracy, residual UNet is a powerful and accurate deep-learning architecture that is ideally suited for land-cover change detection.

In order to maintain spatial information and extract characteristics at various scales, residual UNet employs an encoder-decoder structure with skip links. By enabling the model to learn residual mappings, the inclusion of residual connections can further improve the performance of the model. A lot of information on the land cover and changes through time can be obtained by using remote-sensing imagery. Multi-spectral and temporal data from remote sensing can be used to spot changes in land-cover imagery. The spatial and temporal characteristics of remote-sensing images can be captured by the residual UNet-based technique to detect changes in land cover. The model can learn about feature changes owing to the residual connections, which aids in the recognition of modified pixels. Using the residual UNet-based method to detect land-cover change in remote-sensing images can yield reliable results.

The applications of deep-learning models in satellite imagery can sense the images over different time periods and find the changes in the land cover, such as growth of structures on artificial islands and land reclamations. The detection of land-cover changes is also helpful to provide suggestions to build ports, buildings and roads in artificial-island constructions. These methods are used to detect the changes in the ecosystem, such as coastal erosion, vegetation loss and water bodies. This helps experts plan and identify the progress and make wise decisions accordingly (Suribabu et al., 2014). It also gives an idea about risk management, resource optimization, environment assessment and infrastructure planning.

CONCLUSIONS

This paper uses an encoder-decoder-based deep-learning framework to detect the changes in land-cover images. The residual UNet method effectively aggregates the multiscale features and can find the changes in the images. This workflow consists of three phases: training, testing and evaluation. The work's significant contribution is to enhance the detection capabilities of basic UNet with residual connections. The proposed method is evaluated based on precision, recall, F1-score and accuracy performance metrics. The experimental results show that the proposed method has produced reliable results with no increase in the number of parameters. Furthermore, this work can be extended by incorporating high-resolution input images to check for specific change-detection tasks, such as construting buildings, roads and agriculture areas.

Declaration

We declare that the present work has not been submitted nor considered for publication in other journals.

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